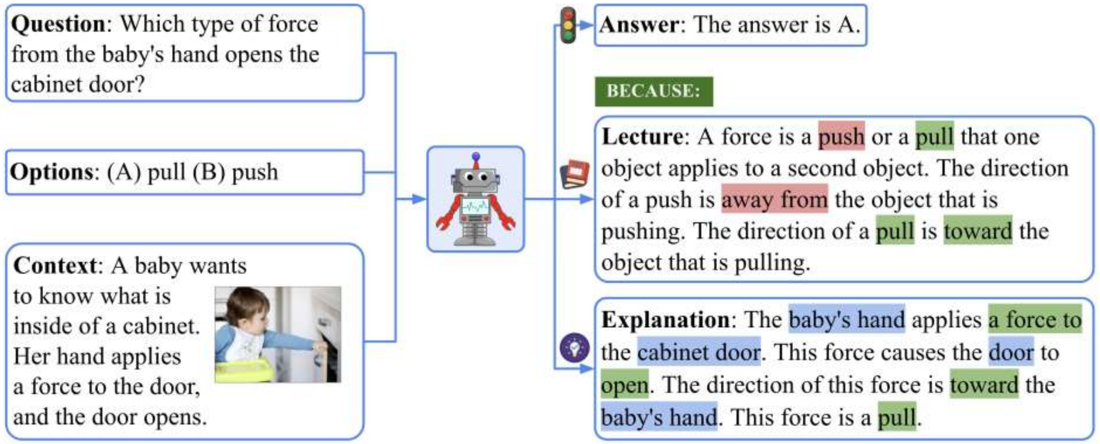
Low Resource Offline Multimodal Chatbot for ScienceQA



Team BOTZZ □

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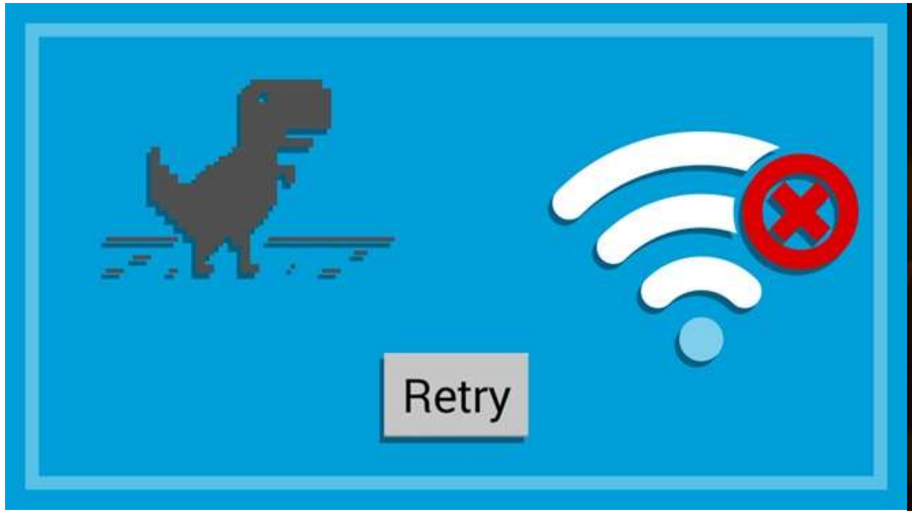
Motivation and Problem Statement

1) Problem 2) Significance 3) Gap 4) Objective

Motivation (1. problem)

Reliance on internet-based resources is not always feasible or desirable due to:

- Connectivity issues
- Privacy and safety concerns
- Distractions



Motivation (2. significance)

Providing a free, accessible (low resource) and offline science learning tool can improve **safety and educational equity**.

1 December 2020 – Two thirds of the world's school-age children – or 1.3 billion children aged 3 to 17 years old – do not have internet connection in their homes, according to a new joint report from UNICEF and the International Telecommunication Union (ITU).

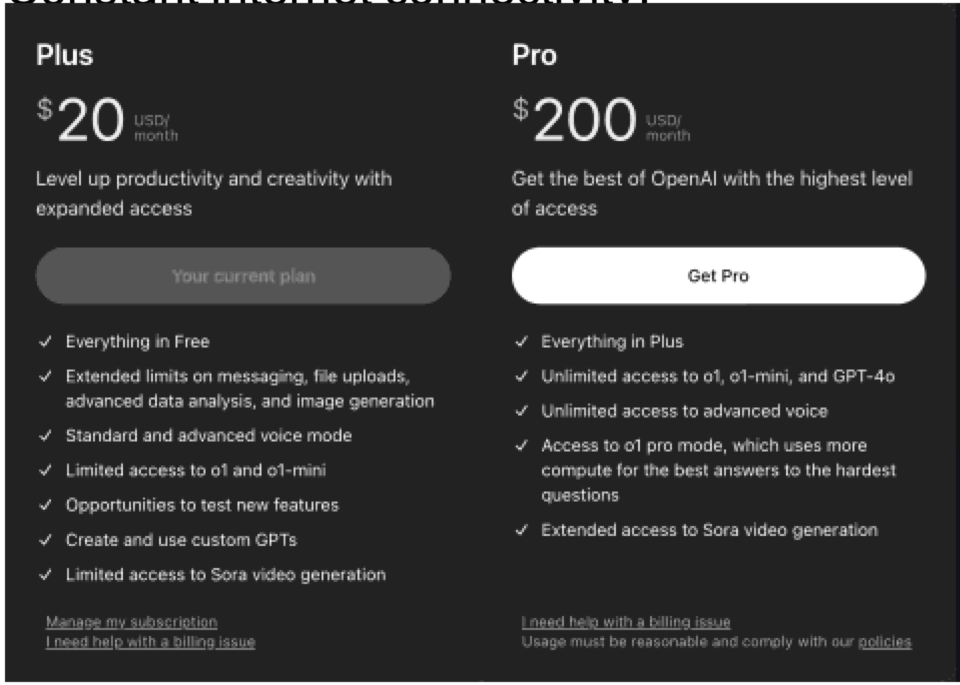
Unicef UK
https://www.unicef.org.uk › press-releases › two-thirds-...

Two thirds of the world's school-age children have no internet ...

Motivation (3. Gap)

There is a lack of specialised science chatbot that run efficiently and entirely offline on personal devices like laptops or mobile phones. While online proprietary state-of-the-art chatbots exist (such as ChatGPT), they rely on:

- Billed APIs
- Data collections
- Constant internet connectivity.



Motivation (4. objective)

To develop a chatbot utilising a low resource open source LLM model (Gemma-3-4B-instruction-tuned) that **operates completely offline on user devices**. Low computational cost

- High accuracy

Literature Review

Literature Review

Introduce **ScienceQA:**A large-scale dataset with questions from science curricula

When a question is enriched with **Chain-of-Thought (CoT)** reasoning we see an improvement in accuracy

Model and prompt type	Accuracy
UnifiedQA with zero-shot	70.12%
GPT-3 with zero-shot	74.04%
UnifiedQA with CoT	74.11 **(3.99↑)**
GPT-3with CoT	75.17 **(1.20↑)**

Learn to Explain: Multimodal Reasoning via Thought Chains for Science Question Answering

Pan Lu[1,3], Swaroop Mishra[2,3], Tony Xia[1], Liang Qiu[1], Kai-Wei Chang[1], Song-Chun Zhu[1], Oyvind Tafjord[3], Peter Clark[3], Ashwin Kalyan[3]
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Abstract

Our project uses **SeienceQA** dataset and **CoT** prompts.

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Literature Review

Introduce Retreival-Augmented Generation **(RAG):**

A hybrid architecture that combines the strengths of **parametric memory** with **non-parametric memory**

This help to:

- Improve factual accuracy and adaptability
- Generated more compatible and flexible information

We are using **retrieval (ChromaDB)** to bring in relevant lecture notes

Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks

Patrick Lewis[†‡], Ethan Perez[*],

Aleksandra Piktus[†], Fabio Petroni[†], Vladimir Karpukhin[†], Naman Goyal[†], Heinrich Küttler[†],

Mike Lewis[†], Wen-tau Yih[†], Tim Rocktäschel[†‡], Sebastian Riedel[†‡], Douwe Kiela[†]

[†]Facebook AI Research; [‡]University College London; [*]New York University;
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Abstract

Literature Review

- Introduce a prompting technique: **Fact-and-Reflection (FaR)**

➢ The technique split the process into

- 1. **Fact generation: Model recall the relevant knowledge**
- **2. Reflection: Model reasons base on the facts**

This help to:

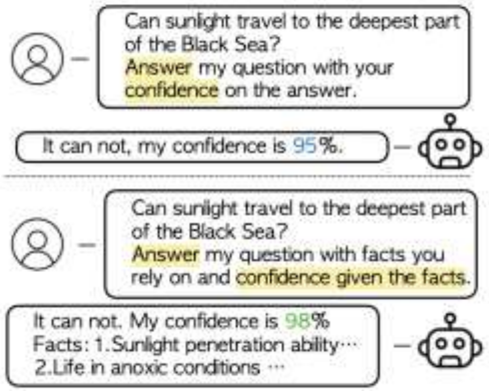
1. Avoid overconfidence and express uncertainty
2. Improve confidence that match the actual correctness
3. Get more trustworthy confidence estimates

Fact-and-Reflection (FaR) Improves Confidence Calibration of Large Language Models

Xinran Zhao[1,2,*] **Hongming Zhang**[1] **Xiaoman Pan**[1] **Wenlin Yao**[1]
Dong Yu[1] **Tongshuang Wu**[2] **Jianshu Chen**[1]
[1]Tencent AI Lab, Bellevue, [2]Carnegie Mellon University

Abstract

For a LLM to be trustworthy, its confidence level should be *well calibrated* with its actual performance. While it is now common sense that LLM performances are greatly impacted by prompts, the confidence calibration in prompting LLMs has yet to be thoroughly explored. In this paper, we explore how different prompting strategies influence LLM confidence calibration and how it could be improved. We conduct extensive experiments on six prompting methods in the question-answering context and we

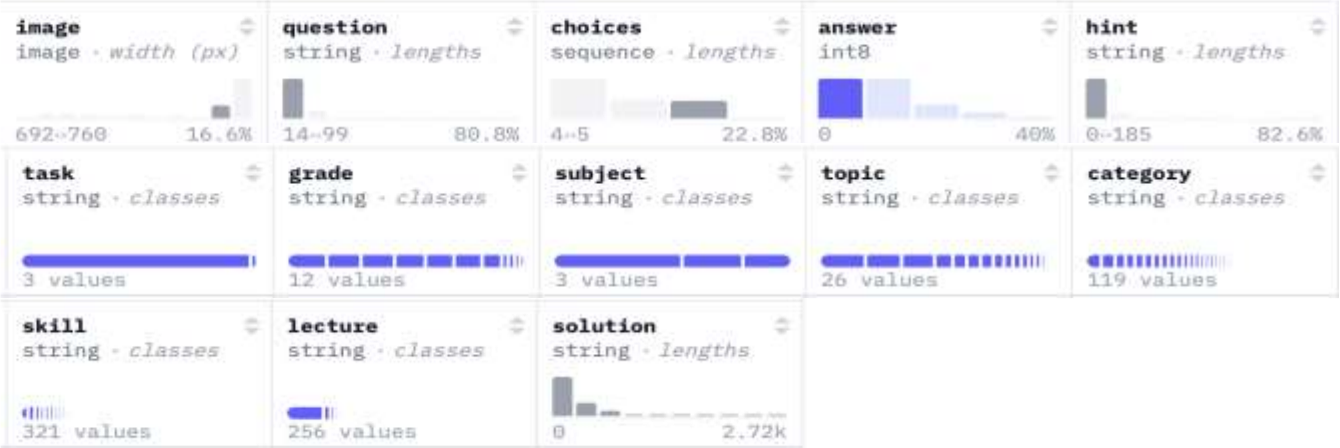


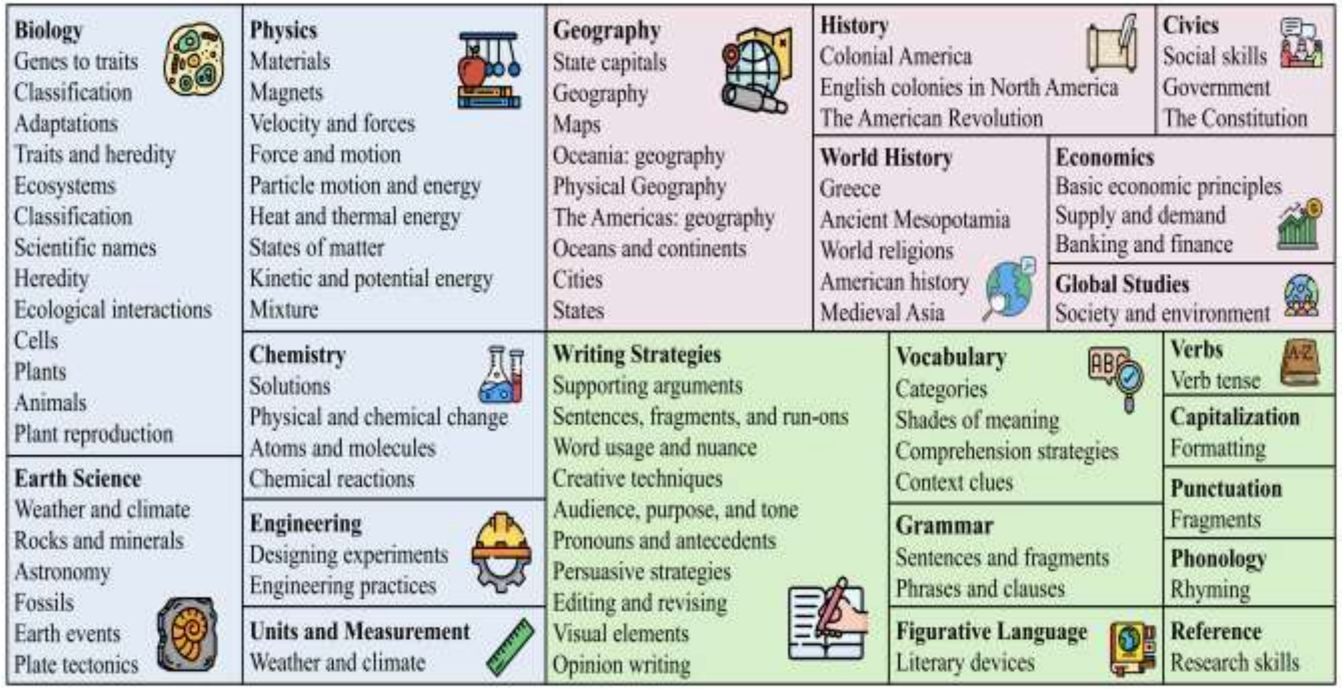
The ScienceQA Dataset

Dataset

➢ScienceQA Dataset

- The top image shows all the different fields in the dataset.
- Bottom image shows all the different topics and categories that the questions in the dataset cover
- This level of variety makes the ScienceQA dataset especially valuable for building general-purpose educational AI systems, or for specialized models focusing on specific school subjects.





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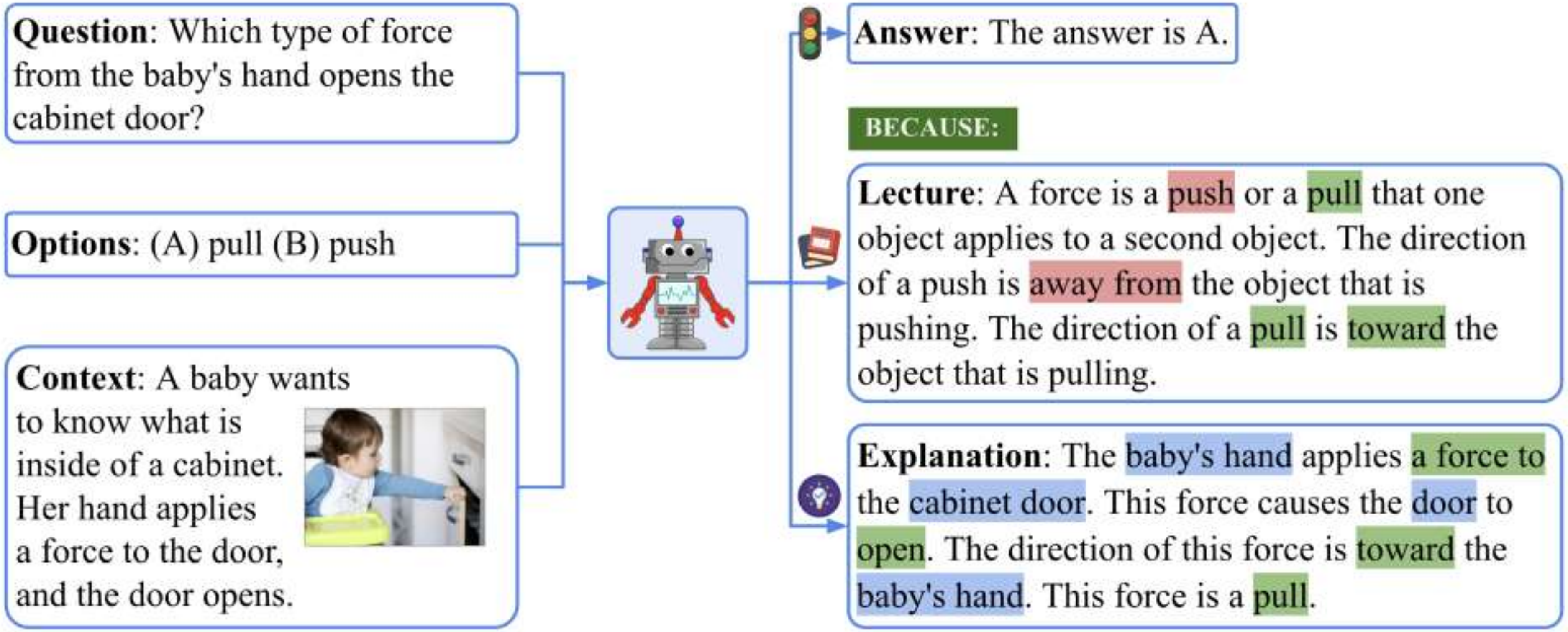
Dataset

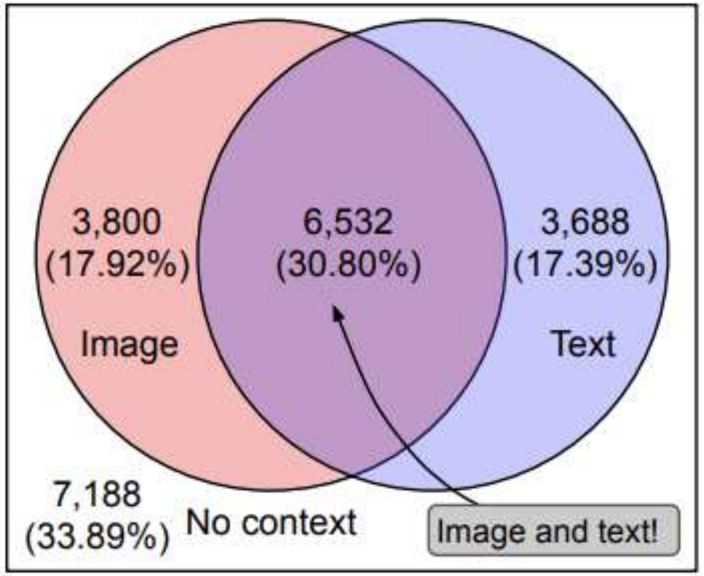
➢ Basic example of how the fields/metadata in the dataset are used



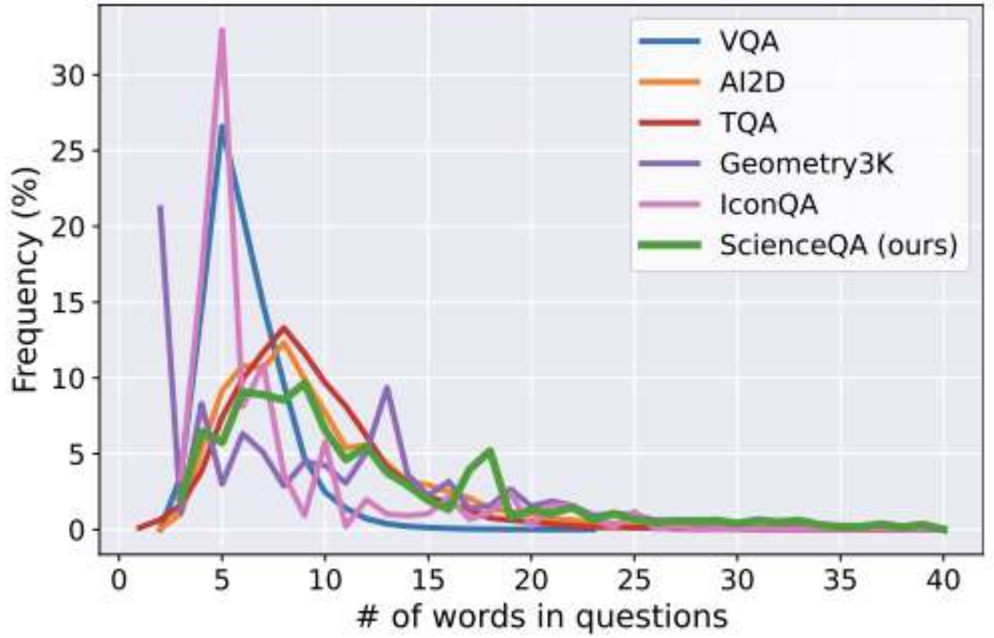
Dataset

➢Data Set Split

Split (3)
✓ train (12.7k rows)
validation (4.24k rows)
test (4.24k rows)



- The dataset has **~21K questions** that are randomly split into training, validation, and test splits with a ratio of **60:20:20**.
- In ScienceQA, (48.7%) have an image context, (48.2%) have a text context, and (30.8%) have both.
- Sometimes, the model is given a lot of information from multiple sources, while at other times, the only source of information is the question itself.



Methods

Methods

1. Experimental Setup & Rationale

- **Objective**: Improve the performance (accuracy and efficiency) of the model with different methods.
- **Dataset**: ScienceQA
- **Platform**: Google Colab

2. Main Methods

- **Fine-tuning**
- **RAG(Retrieval Augmented Generation)**

Fine-tuning

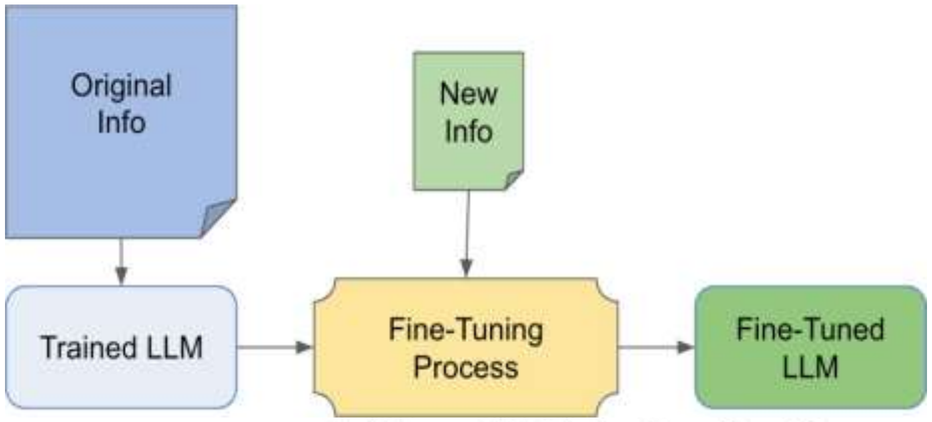
- Use the training and validation set of the data
- Format the data with labels (supervised)
- **PEFT** (parameter-efficient fine-tuning) library by Hugging Face
- LoRA (low-rank adaption)

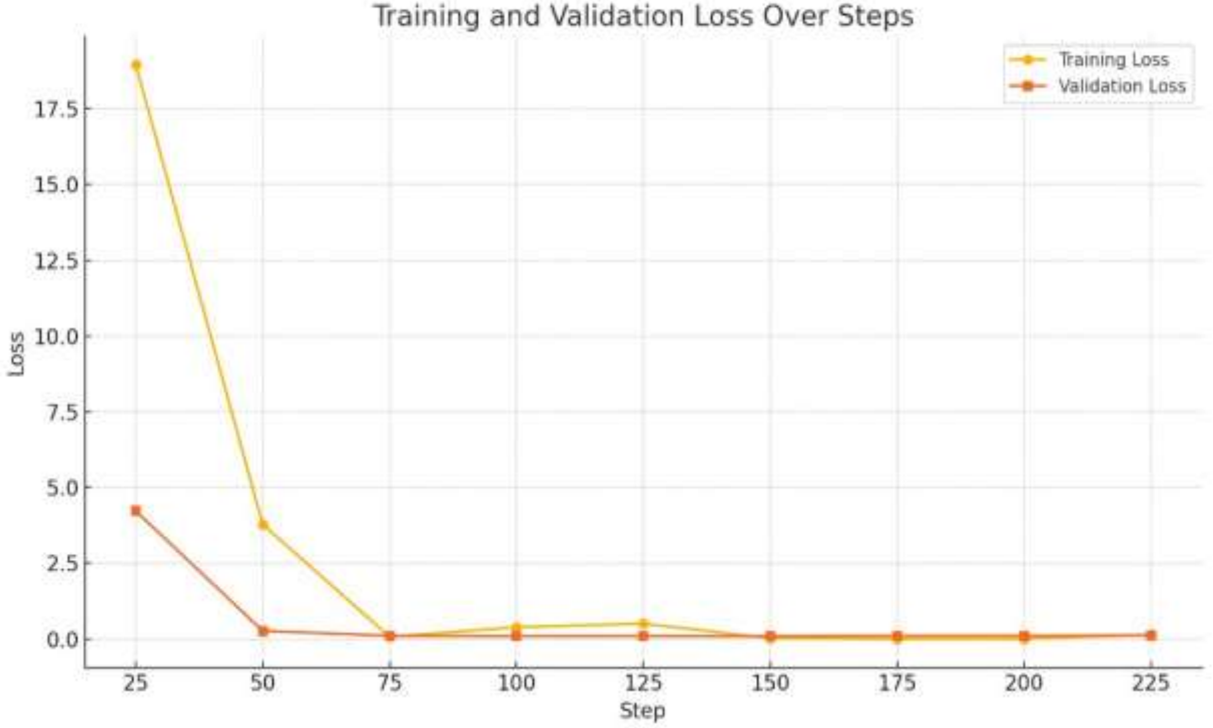
Difficulties:

- Passing text and image (multimodal input) to be tokenised and trained

Drawback:

- Resource intensive -> **not ideal** for minor information updates

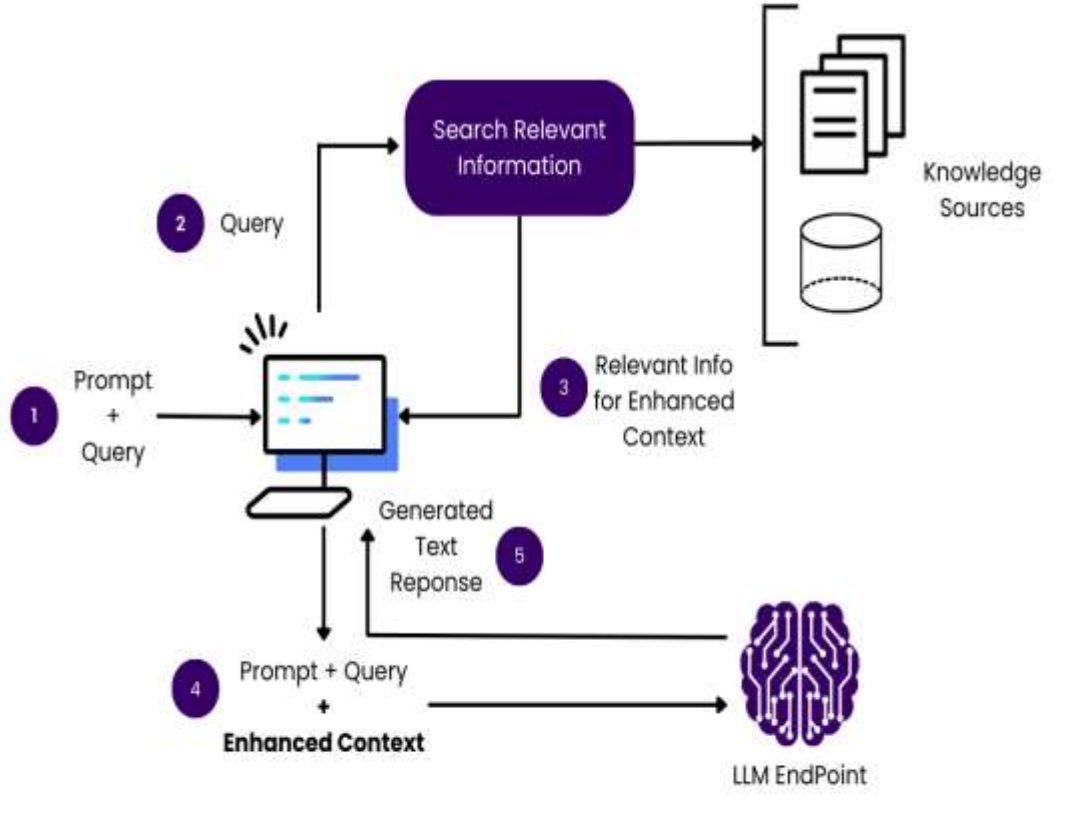




RAG (Retrieval Augmented Generation)

Definition: RAG a technique that enhances the accuracy and relevance of Large Language Models by incorporating external knowledge sources

1. User query
2. Retriever (via vector DB like ChromaDB
   - Converts into embeddings
   - Finds top-k relevant documents based on similarity
3. Augmented prompt
4. Retrieved documents+ original question are passed to LLM
5. Generator:
   - The model (e.g. GPT4o mini) generated a context aware answer.



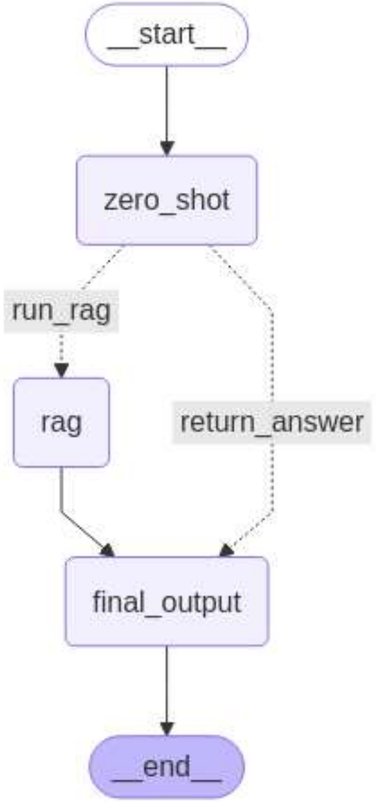
RAG (Retrieval Augmented Generation)

- Sentence-transformers model
  - all-MiniLM-L12-v2
- maps sentences & paragraphs to a 384 dimensional dense vector space and can be used for tasks like clustering or semantic search.

- Vector DB
  - ChromaDB
  - Stores the vectors
  - Retrieve based on vector similarity and metadata

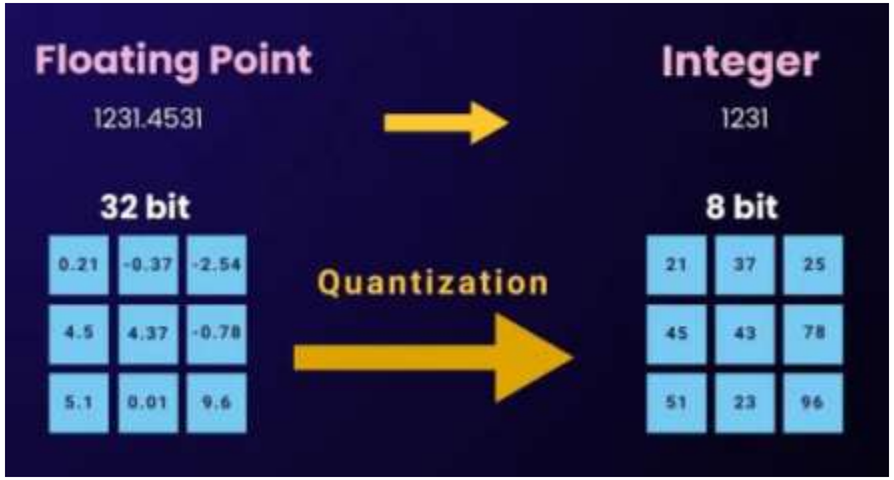
Integration of methods with Langgraph

- ➢Use model's zero shot confidence score to determine if langgraph is need
- ➢High confidence -> return zero shot response
- ➢Low confidence -> run RAG



Quantization

- Load the model with 8-bit integer
- Quantization is a compression technique that involves mapping high precision values to a lower precision one
- Improves efficiency on consumer-grade hardware



Results

Using a subset of the data

1. After initial testing with 4o-mini (minimal prompting) we extracted a **subset of the training dataset** which contained 490 questions that 4o-mini got wrong. This is **12%** of the training set.
2. We used this subset (the ”difficult” questions) to test various methods.

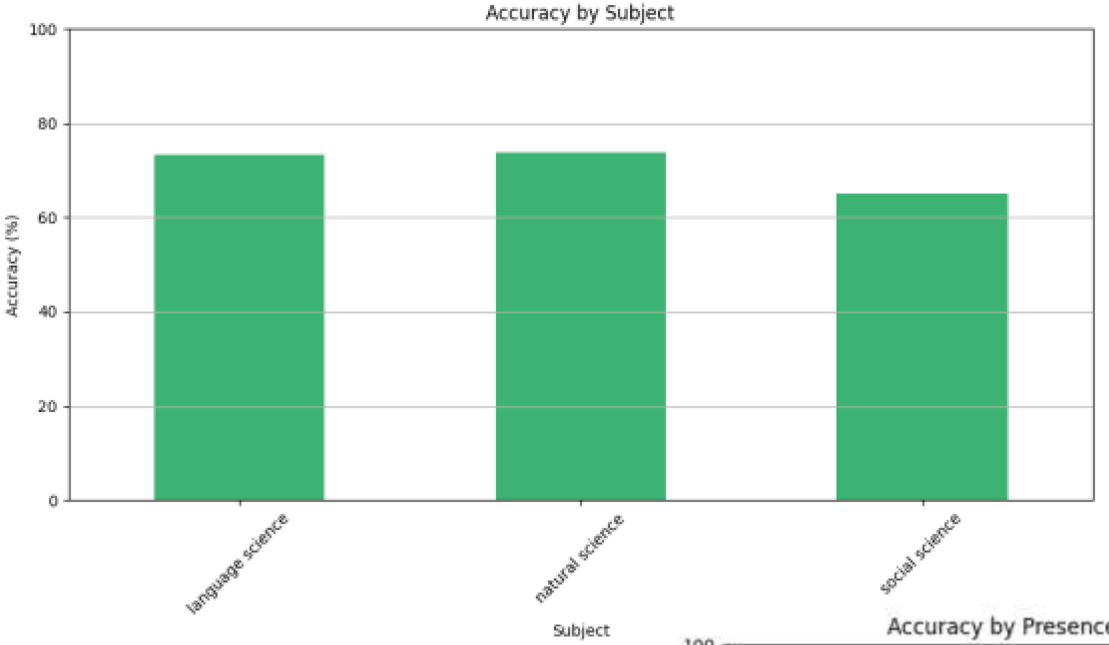
Results

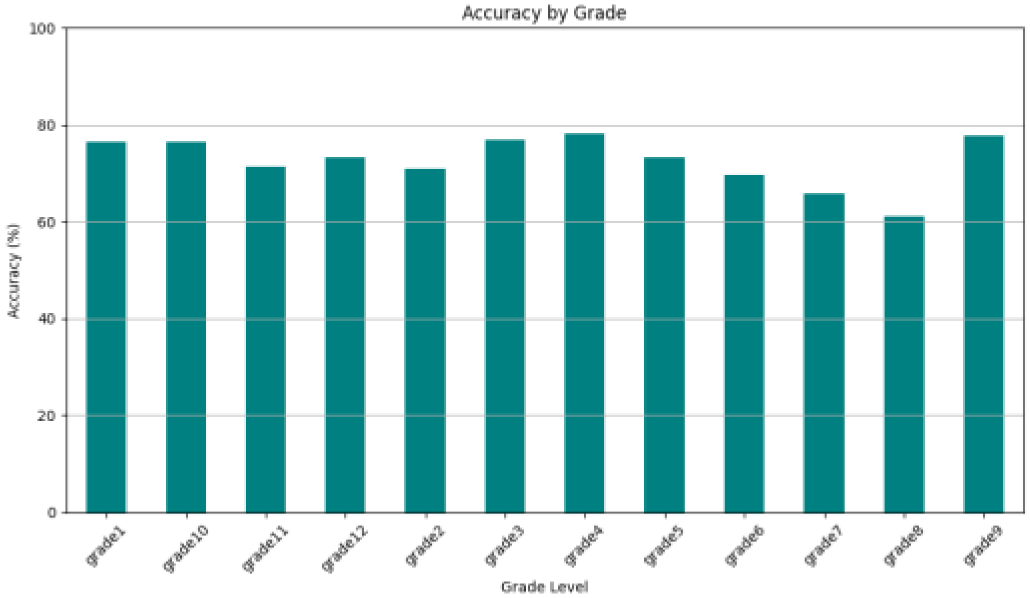
(no fine tuning, zero-shot vs RAG)

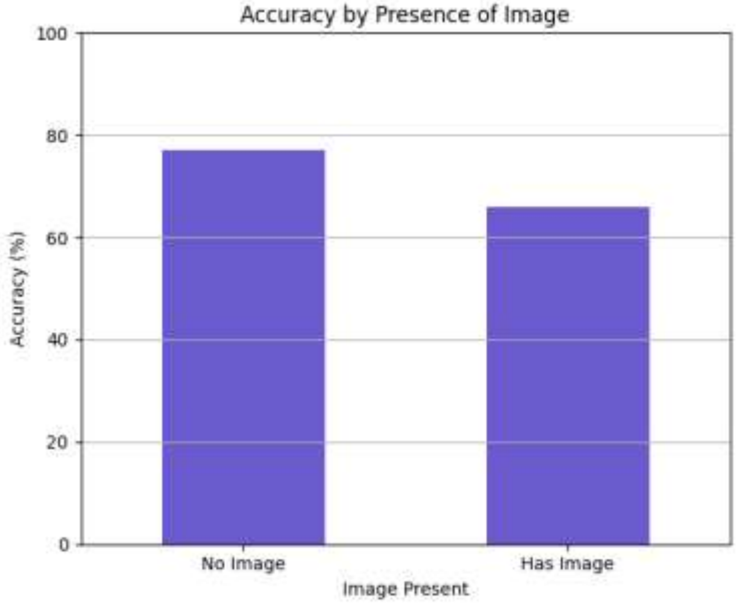
Model Name	Accuracy (on “difficult” questions subset size=490)
GPT-4o	49.28%
Gemini-2.0-Flash	55.21%
Gemini-2.0-Flash (with RAG #1)	60.82%
Gemini-2.0-Flash (with RAG #2)	57.96%
Gemini-2.0-Flash-Lite	56.03%
Gemini-2.0-Flash-Lite (with RAG #1)	58.75%
Gemini-2.0-Flash-Lite (with RAG #2)	58.78%

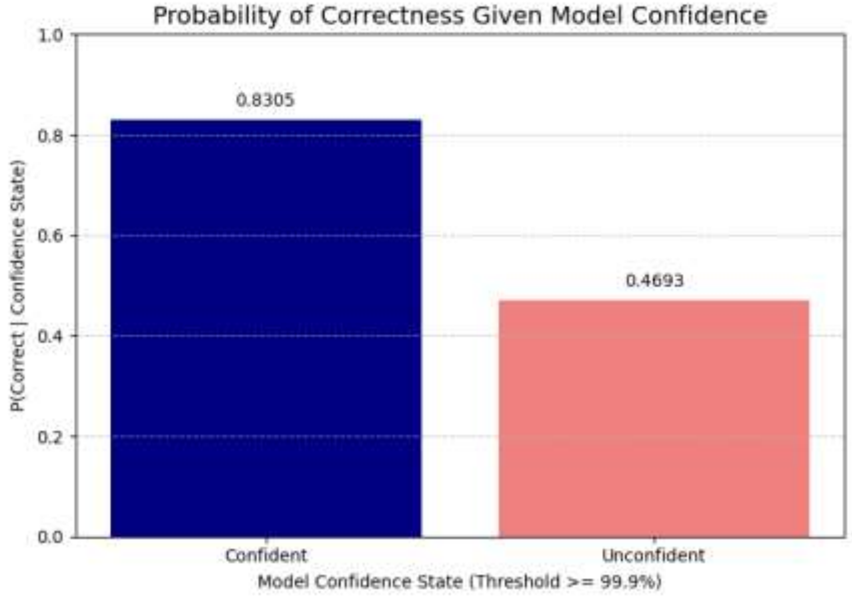
RAG method #	K (retrievals)	Embedding Method	VectorDB Size
1	1	text-embedding-3-large	12726
2	1	sentence-transformers/all-MiniLM-L12-v2	234 (deleted duplicates)

Data Analysis (Using gemma-3-4b it with minimal prompting)



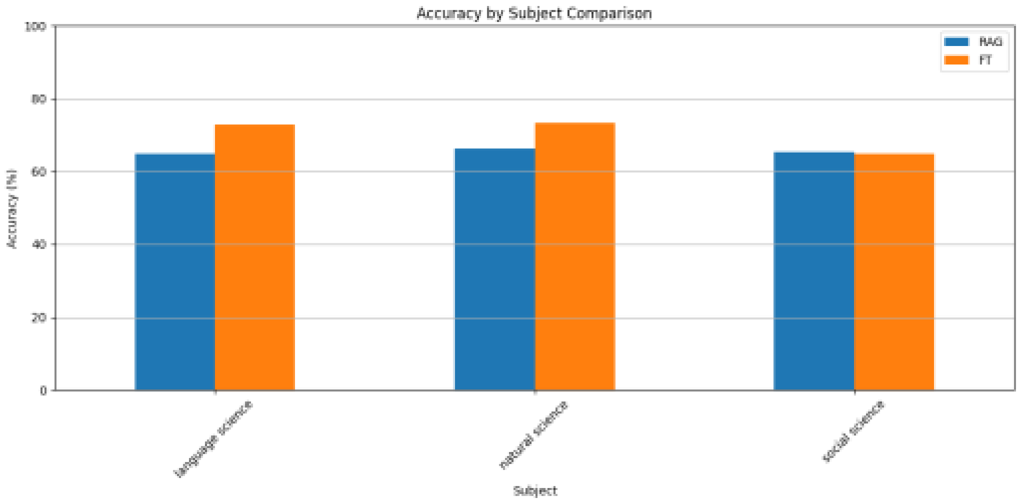


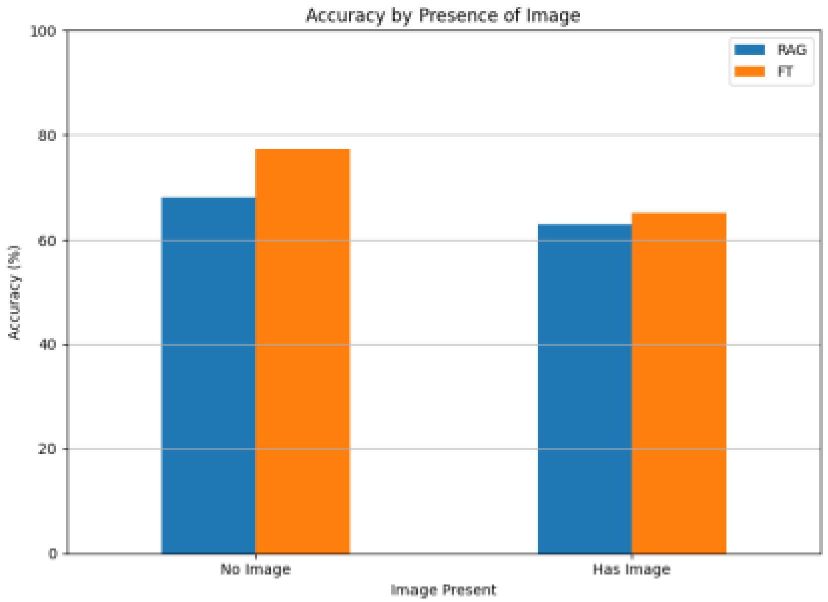


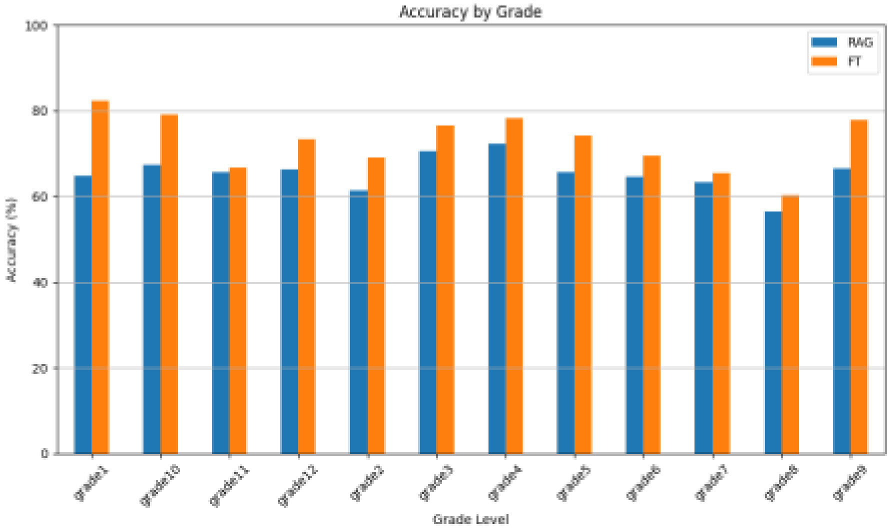


Results – RAG vs Fine tuned

Model Name	Accuracy
RAG	65.64%
Fine Tuned	71.52%







Data Analysis

- Found a correlation between confidence and accuracy.
- When >99.9% confident, accuracy is Base : 83%, FT : 84%
- When <99.9% confident, accuracy is Base : 47%, FT : 47%

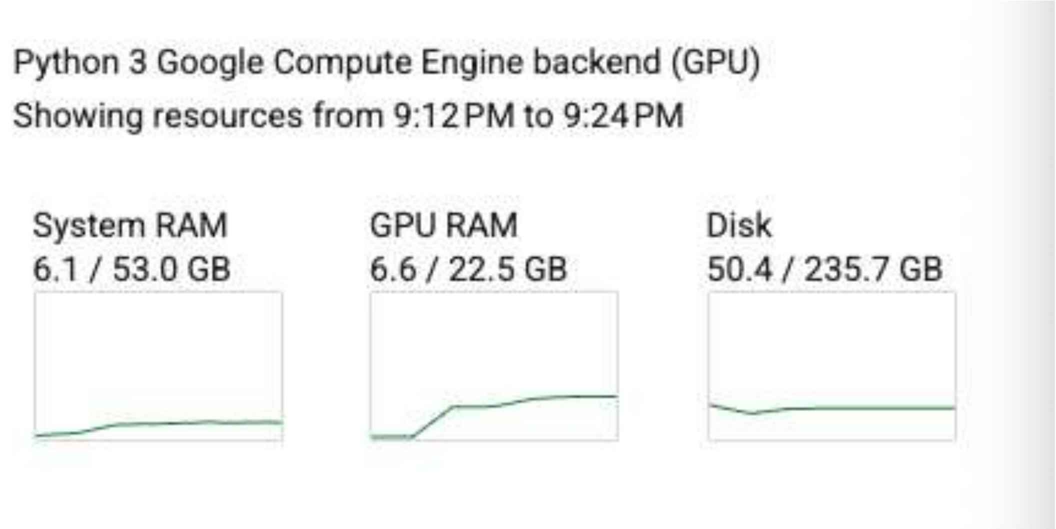
```
P(correct | confident): 0.83
P(correct | unconfident): 0.47
```

Gemma 4B it Base model
Confident threshold: confidence>0.999

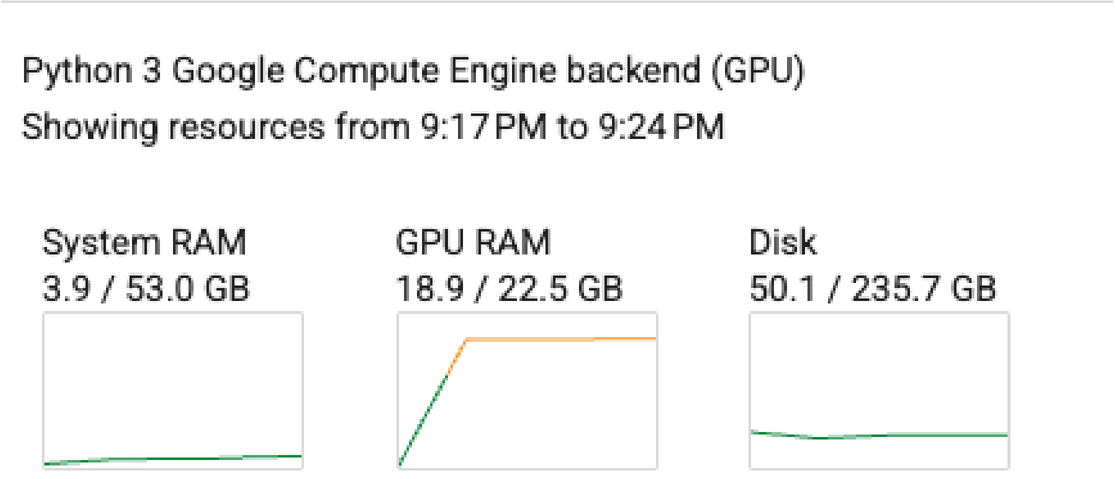
```
P(correct | confident): 0.84
P(correct | unconfident): 0.47
```

Gemma 4B it Fine Tuned
Confident threshold: confidence>0.999

RAM usage quantized vs Full Size



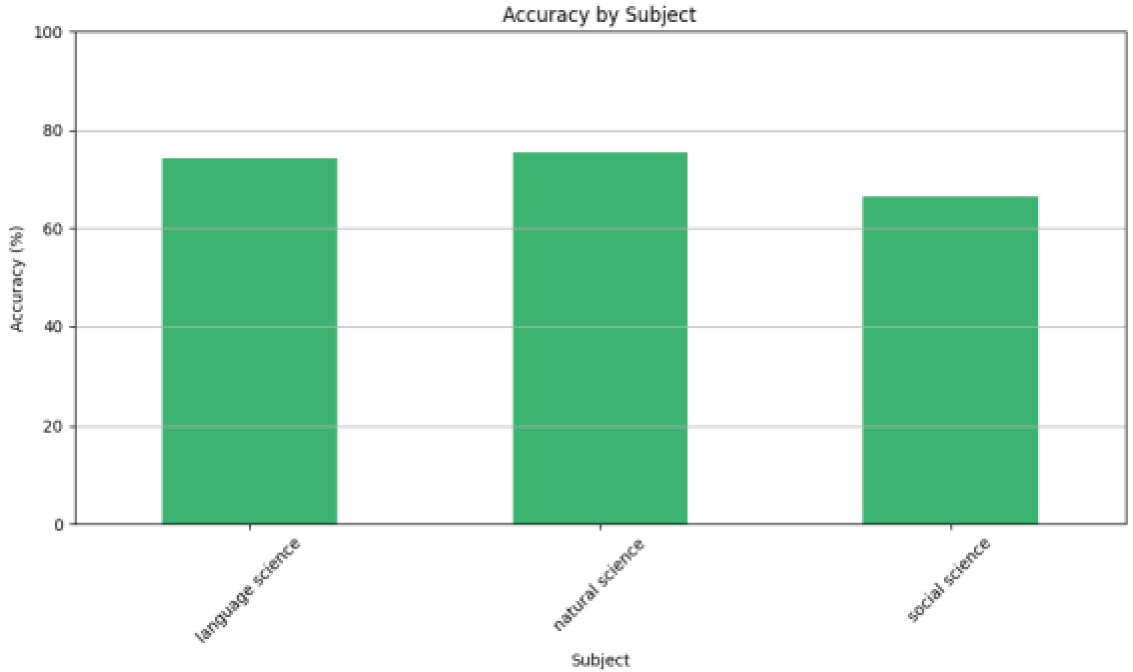
Gemma 4B quantized

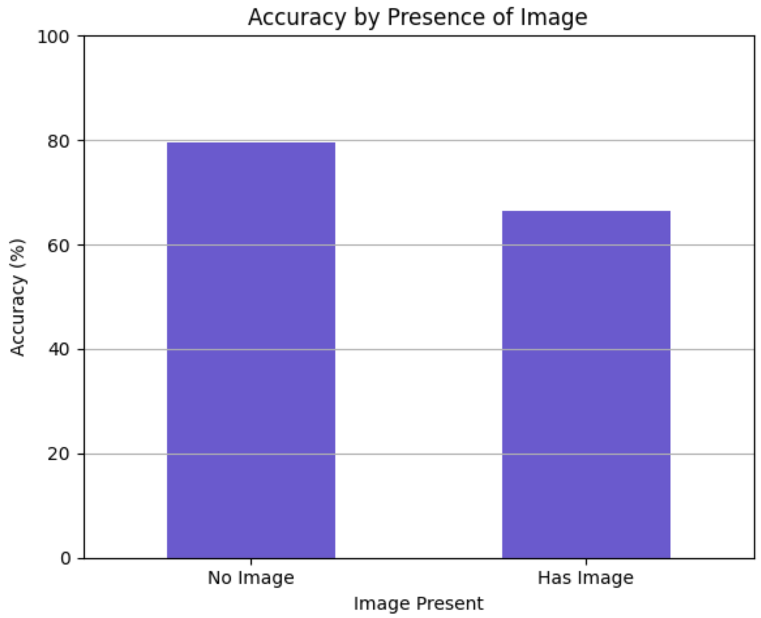


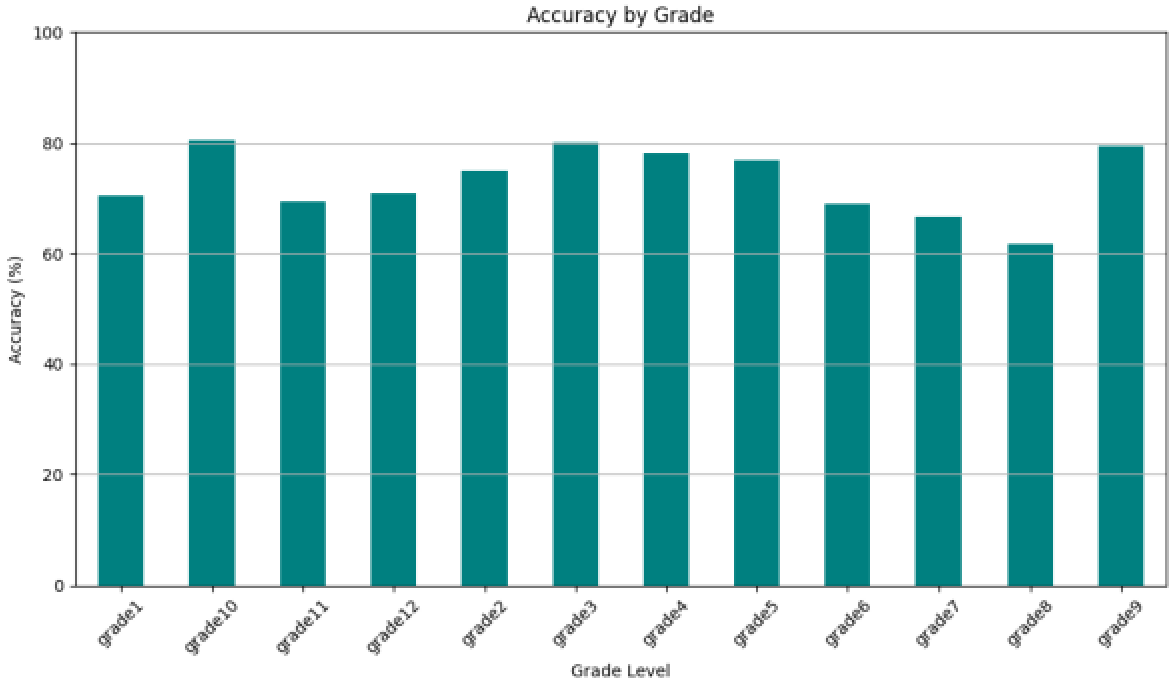
Gemma 4B full size

Mixed Method

Model Name	Accuracy
Mixed Quantised	73.31%







Gemma 3 Variant	Accuracy on test set
Fine tuned mixed methods quantised	73.31% (0.10 ↑)
Base model zero shot quantized	73.21%

Discussion and Conclusion

Discussion and Conclusion

- Gemma 3-4b performed significantly worse with RAG
  - Small models like Gemma 3–4B can’t handle long retrieved documents effectively
  - Small models are more affected by minor changes in how prompts and context are phrased
  - Quality of the prompt can significantly impact the output
- RAG is a contingency for when the model has low confidence
- Quantising the data reduces the RAM usage (makes it computationally less expensive)
- Our Fine Tuning did not improve the model's performance by much.